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# Solving an assignment–selection problem with verbal information and using genetic algorithms [1]

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**Abstract**

The assignment–selection problems deal with finding the best one-to-one match for each of the given number of "candidates" to "positions". Different benefits or costs are involved in each match and the goal is to minimise the total expense. In this paper we propose the use of verbal information for representing the vague knowledge available. Doing it, natural linguistic labels allow the problem to be recognised as it is in real life. This paper is an attempt to supply a satisfactory solution to real assignment–selection problems with verbal information and using genetic algorithms, showing the application of this model to the staff selection problem. 

*Keywords:* Assignment problems; Selection problems; Relationships; Linguistic variables; Fuzzy numbers; Genetic algorithms; Staff selection

## 1. Introduction

The assignment problems appear in some decision-making situations. The typical problems are to assign tasks to machines, workers to jobs, salesmen to regions, requirements to suppliers, etc. The main characteristic of these kinds of problems is that only one candidate, task, worker, etc., is assigned to each position, machine, regions, etc. In particular, we search for the set of assignments–selections that optimise the considered target. In particular, we search for the set of assignments or selections that optimise the considered target, where it is possible to have a number of tasks or worker greater than the number of machines or jobs, calling it as assignment–selection problem.

The main characteristics of the problem are the following:

1. The objects under consideration are finite, such as service, teams, jobs, employees.
2. The objects have to be assigned–selected on a one-to-one basis to other objects.
3. The results of each assignment–selection can be expressed in terms of payoffs such as cost of profits.

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4. The objective is to assign–select objects in such a way that the total cost is minimised or the total profit is maximised.

Traditional assignment problem is a well-known, NP-hard combinatorial problem which involves finding the optimum of the linear assignment function subject to various linear restrictions (Wagner, 1975). Moreover, all the information required is exactly known.

In many cases of real life assignment–selection problems, there are situations in which the total cost or profit obtained is not equal to the sum of the individual assignments. This is due to the relations that the objects assigned have, can produce synergetic effects. So, for example, in a staff selection problem we can select the best individuals for each job, but if the posts are related, we must take into account to obtain a "good team".

On the other hand, the information available could not be precise or exact. Ever more we can manage imprecise information represented as verbal information, that is, linguistic information represented as linguistic variables such as opinions, thinking, beliefs, notion, feelings, etc.

An effort to collect and evaluate all this information arouses interest in the possible application here of the Fuzzy Sets Theory (Zadeh, 1965; Kaufmann, 1975; Zimmermann, 1985) with the aim of being able to handle suitably the uncertainty which is characteristic of the decision-making processes in assignment–selection problems. This paper specifically proposes the use of linguistic variables (Zadeh, 1975) to represent the information on the variables and lead to a decision-making model which is able to handle such information. Based on the associated membership functions, we propose a decision model for obtaining a fuzzy evaluation of the solutions and they are compared though *fuzzy distance* (Kaufmann and Gil-Aluja, 1987).

To optimise the assignment or selection envisaged, is necessary some tool capable of grasping all the complexity which vague information brings with it, as is also the case if the decision-maker is to reach a good solution. Thus, for the purposes of this paper we suggest using a genetic algorithm (GA) (Goldberg, 1989; Biethahn and Nissen, 1995; López-González et al., 1995, 1998). The reason for this is that it is a heuristic method of searching solutions and so does not impose restrictions upon the posing of a problem, however complex it may be. In this study, the algorithm is characterised by its use of a fitness function that allows the evaluation of linguistic information.

Trying to demonstrate the practical application of this model, we include a real life problem. This one present a staff selection problem that may show how frequent are the approaches suggested here.

In the light of the above, Section 2 offers an introduction to linguistic information management. Section 3 shows a descriptive analysis of the assignment–selection problem and the linguistic model proposed. Thereafter the GA designed to achieve a good solution to the problem is presented in Section 4. Section 5 shows some applications to the model and, after that, a practical example, the staff selection problem. The final section includes some concluding remarks.

## 2. Linguistic information

Usually, in a quantitative situation the information is expressed as numerical values. However, when working in qualitative areas, which are characterised by vague or imprecise knowledge, the information cannot be set out in a precise numerical way. Thus, it would be a more realistic approach to use linguistic information instead of numbers, provided that the variables involved in the problem lend themselves to expression in this manner (Zadeh, 1975). This way of looking at things can be applied to a wide range of problems, since it allows information to be represented in a more suitable fashion (Delgado et al., 1993; Yager, 1995; Herrera et al., 1995).

This paper supports the possibility of establishing in linguistic terms the needed information. It would appear clear that an expert might not know in a precise numerical way the level of a candidate to be placed on the several positions, but could indicate it in linguistic terms. To estimate the information, it has been chosen to use a set of nine linguistic labels, which are shown in Fig. 1.

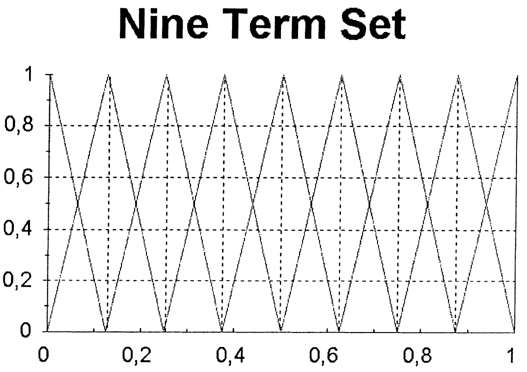


Fig. 1. Linguistic term set.

Thus, the labels and the triangular fuzzy numbers associated with them are the following:

| | |
|---|---|
| Essential | $(0.875, 1, 1)$ |
| Very high | $(0.75, 0.875, 0.1)$ |
| Fairly high | $(0.625, 0.75, 0.875)$ |
| High | $(0.5, 0.625, 0.75)$ |
| Moderate | $(0.375, 0.5, 0.625)$ |
| Low | $(0.25, 0.375, 0.5)$ |
| Fairly low | $(0.125, 0.25, 0.375)$ |
| Very low | $(0, 0.125, 0.25)$ |
| Unnecessary | $(0, 0, 0.125)$ |

We propose to use these triangular fuzzy numbers as a representation of the labels semantic. Obviously, other semantic of the functions could be considered (Herrera and Herrera-Viedma, 1999).

## 3. Assignment–selection problems

In this section we are going to introduce the mathematical representation of the linguistic assignment–selection problem, we propose a methodology to evaluate the possible solutions, and therefore we present a search method for finding a good solution by means of genetic algorithms.

### 3.1. Fuzzy-linguistic approach for assignment–selection problems

In order to show a practical point of view we develop the model proposed with one general assignment–selection problem. We are going to explain the problem that is to select candidates (jobs, staff, suppliers, salesmen, etc.) to positions (machines, posts, requirements, regions, etc.). Each position can be characterised by necessary skills to develop it. Each skill has his own importance grade, not all the same. Also, each position can be related with others and with importance level. To cover these positions we have to assign–select the most accurate candidates from a set of them, according to their skill levels and relationships. The generalisation to assign problems is the following:

(1) *Positions and skills*. Step 1 is to determine for what positions are to be recruited or to which positions existing candidates are to be assigned (names).

$$X' = (X'_1, X'_2, \ldots, X'_{m1}).$$

Associated with each position we know the skills required and note the global vector as

$$Sk = (Sk_1, Sk_2, \ldots, Sk_{m2})$$

together with the weighting that each skill has for the various positions.

$$IC = \begin{pmatrix} IC_{11}, \ldots, IC_{1m2} \\ \vdots \\ IC_{m11}, \ldots, IC_{m1m2} \end{pmatrix}, \quad IC_{ij} \in W.$$

For the feature weighting, the labels that are proposed are the following:

$$W = \{\text{Essential, Very high, Fairly high, High Moderate, Low, Fairly low, Very low, Unnecessary}\}.$$

In addition, when candidates are being selected for several positions, the expert or decision-maker may consider that not all of the positions have the same weighting, and prefer solutions aimed at putting the most suitable candidate into the most crucial positions. For this reason, a label associated with each position must be included to show the weighting that the position has for the recruitment procedure, which is under way. This characteristic is defined in this paper in exactly the same way as skill requirements, that is, with nine labels.

$IP = (IP_1, IP_2, \ldots, IP_{m1}), \quad IP_i \in W.$

Moreover, since the positions are not independent of one another, the links between them should be analysed, as also the weighting of such links. Here, too, the use of nine labels is felt appropriate.

$$RP = \begin{pmatrix} -, RP_{12}, \ldots, RP_{1m1} \\ \vdots \\ RP_{m11}, \ldots, RP_{m1m1-1}, - \end{pmatrix}, \quad RP_{ij} \in W.$$

(2) *Candidates levels and relationships*. Once the positions have been characterised, then candidates are considered, denoted from 1 to $n$. Information relating to them includes two types:

- the operational levels, which they develop in the varying skills needed for the positions,

$$N = \begin{pmatrix} N_{11}, \ldots, N_{m2} \\ \vdots \\ N_{n1}, \ldots, N_{nm2} \end{pmatrix}, \quad N_{ij} \in LL,$$

with the next set of labels associated:

$LL = \{$Optimum, Very high, Fairly high, High, Moderate, Low, Fairly low, Very low, Lowest$\}$;

- the relationships linking candidates with one another

$$RC = \begin{pmatrix} -, RC_{12}, \ldots, RC_{1n} \\ \vdots \\ RC_{n1}, \ldots, RC_{nn-1}, - \end{pmatrix}, \quad RC_{ij} \in R,$$

with the next set of labels associated:

$R = \{$Excellent, Very good, Fairly good, Good, Indifferent Bad, Fairly Bad, Very bad, Vile$\}$

(3) *Criteria preference*. Using this approach, it comes down to a problem of optimisation using imprecise information and having two aims or criteria:

- good candidate levels in the skills needed for the positions and
- good relationships among candidates for linked positions.

Due to this, the decision-maker must decide what criterion has a higher importance. We propose to allocate a linguistic label of importance, $W$, to each criterion $(P_c, P_r)$.

Although we have described different term sets for each variable, in order to operate with them, taking into account that all of these sets have the same number of labels and all of them have the same membership functions presented in Section 2, the sets of labels will be changed to the first one from an operative point of view assuming a general label set $L = \{l_0, l_1, \ldots, l_8\}$. Thus, the corresponding transformation would be, for example, $l_3$ equivalent to *Bad* ($R$), *Low* ($LL$) and *Low* ($W$), and so on.

### 3.2. Fuzzy-linguistic decision model for assignment–selection problems

In the resolution of assignment–selection problems it is necessary to evaluate the solutions in order to obtain the better one. In this paper, for evaluating the solutions we propose a model that uses the semantic of fuzzy numbers representing the linguistic labels.

Let $S = (S_1, S_2, \ldots, S_{m1})$, be a solution randomly generated for a problem with $m1$ positions, where each $S_j$ belongs to candidate set, being $S_j$ the number associated with the candidate. According to the aforementioned criteria, the proposed decision model has the following steps.

*Step 1. Competence on the positions*. With this step we pretend to obtain a valuation of the solution suitability to position requirements. To this, we propose the following two steps:

*Step 1.1. Competence of each candidate*. For each position there are $m2$ skills which define it, with $m2$ degrees of importance for each skill. Thus, to assess the suitability of each person for each position a link must be established between the level the person has of a given skill and the weight assigned to that skill for the job. To achieve this, the proposal is to multiply each fuzzy number associated with the weighting of each skill by the fuzzy number attributed to the level that the person has in that skill, then add up the results of this multiplication, approximated as triangular fuzzy numbers (Dubois and Prade, 1980).

$$\tilde{g}_i = \sum_{j=1}^{m2} I\tilde{C}_{ij} \cdot \tilde{N}_{S_i j}, \quad i = 1, \ldots, m1,$$

being $I\tilde{C}_{ij}$ and $\tilde{N}_{S_i j}$ the triangular membership functions associated to $IC_{ij}$ and $N_{S_i j}$, respectively.

*Step 1.2. Competence of the solution.* By taking the step outlined above, it is possible to obtain a fuzzy number setting a value on the suitability of each candidate relative to each position. However, the intention is to give an overall value covering the suitability of candidates to positions that will include the fact that the various positions are themselves of different levels of importance. In view of this, it is proposed that the triangular fuzzy numbers for the skills of each candidate should be multiplied by the importance assigned to each position, then add them up, so that the solution as to suitability for positions may be obtained in the form of a triangular fuzzy numbers.

$$\tilde{z}_S = \sum_{i=1}^{m1} I\tilde{P}_i \cdot \tilde{g}_i.$$

*Step 2. Relationship.* The goodness of the solutions will also be determined by the relationships between the candidates included in them. To obtain it we propose the following two steps:

*Step 2.1. Candidate relationship.* On the one hand, the connections between positions are known, as is the weighting for each, and on the other the relationships between candidates are known. So, a link is established for each position between the weighting of its connections to other positions and the degree of relationship that the candidate allocated to the position has with candidates for related positions. To achieve this, the proposed method would be to multiply the triangular fuzzy numbers associated with the weighting of a link between one position and the others by the level of relationship that the person in the position has with the people assigned to related positions.

$$\tilde{g}'_i = \sum_{j=1}^{m1} R\tilde{P}_{ij} \cdot R\tilde{C}_{S_i S_j}, \quad i = 1, \ldots, m1.$$

*Step 2.2. Solution relationship.* Once this has been done, a fuzzy number setting a value on the relationships between each candidate and the rest can be obtained. To set a value on the overall solution, the proposal is to add up all the relationships between all the candidates involved in it.

$$\tilde{t}_S = \sum_{i=1}^{m1} I\tilde{P}_i \cdot \tilde{g}_i.$$

*Step 3. Criteria preference.* Finally, the intention is to add the level of skill to the degree of relationship of the solution, so as to get a single value for the goodness of selection that the solution represents. In this phase the decision maker preferences must be taken into account, in order to assign more weight to candidates' suitability for positions or to candidates' relationships. To this we propose multiply each preference labels for the competence and relationship, respectively, acting the preference labels as weights, and adding the results that indicates the fitness of the solution.

$$\tilde{v}_S = \tilde{P}_C \cdot \tilde{z}_S + \tilde{P}_R \cdot \tilde{t}_S.$$

Once we have an evaluation model, we need some tool that allows us to obtain the best assignment–selection. Trying to do this and taking into account that the approach proposed is not a linear one, we suggest using a GA.

## 4. Genetic algorithms for assignment–selection problems under linguistic valuations

In this section, first we present a short introduction to GAs and after that, the proposal of the biobjective GA is introduced.

### 4.1. Genetic algorithms

GAs are general-purpose search algorithms which use principles inspired by natural genetics to evolve solutions to problems (Holland, 1975). The basic idea is to maintain a population of chromosomes, which represents candidate solutions to the concrete problem being solved, which evolves over time through a process of competition and controlled variation. GAs have got a great measure of success in search and optimisation problems. The reason for a great part of this success is their ability to exploit the information accumulated about an initially unknown search space in order to bias subsequent searches into useful subspaces. This is their key feature, particularly in large, complex and poorly understood search spaces, where classical search tools are inappropriate, offering a valid approach to problems requiring efficient and effective search techniques.

A GA starts off with a population of randomly generated *chromosomes* (solutions), and advances toward better *chromosomes* by applying genetic operators modelled on the genetic processes occurring in nature. The population undergoes evolution in a form of natural selection. During successive iterations, called generations, chromosomes in the population are rated for their adaptation as solutions, and on the basis of these evaluations, a new population of chromosomes is formed using a selection mechanism and specific genetic operators such as *crossover* and *mutation*. An *evaluation or fitness function* must be devised for each problem to be solved. Given a particular chromosome, a possible solution, the fitness function returns a single numerical fitness, which is supposed to be proportional to the utility or adaptation of the solution represented by that chromosome.

GAs may deal successfully with a wide range of problem areas, particularly in management applications (Biethahn and Nissen, 1995). The main reasons for this success are: (1) GAs can solve hard problems quickly and reliably, (2) GAs are easy to interface to existing simulations and models, (3) GAs are extendible and (4) GAs are easy to hybridise. All these reasons may be summed up in only one: GAs are *robust*. GAs are powerful in difficult environments where the space is usually large, discontinuous, complex and poorly understood. They are not guaranteed to find the global optimum solution to a problem, but they are generally good at finding acceptably good solutions to problems quickly. These reasons have been behind the fact that, during the last few years, GA applications have grown enormously in many fields.

The basic principles of GAs were first laid down rigorously by Holland (1975), and are well described in many books, such as Goldberg (1989) and Michalewicz (1996).

### *4.2. A genetic algorithm for assignment–selection problems*

Some authors have applied genetic algorithms to assignment problems (Tate and Smith, 1995; Chu, 1997). In many cases they solve linear problems and use quantitative information. Our approach combines linguistic information and can use a candidate number greater than the number of positions, that supposingly differs from the other ones. Therefore, the GA components are as follows.

#### *4.2.1. Genetic representation*

In this paper the GA has as its principal characteristic the order codification of the solutions. Chains of candidates are generated of the same size as the number of positions available. Two types of problems are distinguished:

- *assignment*, in which the number of positions is the same as the number of candidates, and
- *selection* in which the number of candidates is greater than the number of positions.

An example of a solution for a case of five positions with five candidates available to fill them (assignment) would be:

$$S = (2, 4, 1, 3, 5).$$

This solution indicates that candidate no. 2 comes in the first place and is assigned the first job, $S_1 = 2$; no. 4 comes in second place and gets the second job, $S_2 = 4$; no. 1 gets job 3, $S_3 = 1$; no. 3 gets job 4, $S_4 = 3$; and no. 5 job 5, $S_5 = 5$.

Once the coding has been decided upon, random processes generate a battery of these solutions.

#### *4.2.2. Fitness function*

To work out the suitability of solutions, the fuzzy evaluation model described in the previous section is used. From this a fuzzy number is obtained as an indicator of the goodness of each solution. To set up a hierarchy among them, the proposal is to use the fuzzy distance (Kaufmann and Gil-Aluja, 1987) each one is from the origin (singleton 0), which is defined as follows:

$$d(\tilde{A},\tilde{B}) = \int_{\alpha=0}^{1} \left(\left|A_{\alpha}^{1} - B_{\alpha}^{1}\right| + \left|A_{\alpha}^{2} - B_{\alpha}^{2}\right|\right) \mathrm{d}\alpha,$$

where $[A_{\alpha}^{1}, A_{\alpha}^{2}]$ is the confidence interval of $\tilde{A}$ at the signification level $\alpha$.

*4.2.3. Selection of "parents"*

The next step is the selection, by means of a *Roulette Selection Ranking* (Goldberg, 1989), the most suitable individuals, which will become the "parents" of the next generation.

*4.2.4. Crossover operator*

Traditional crossovers cannot be used for crossing the "parents", because these are an ordered list, and besides we have two different situations. According to this we propose two different crossover operators:

- *Assignment problems*: option taken is the use of Order Crossover (OX) (Goldberg, 1989), which conforms with the need for the solutions generated by it to continue to be feasible responses to the problem.
- *Selection problems*: we propose to use a special *uniform* crossover designed to keep the solutions resulting as feasible ones. The steps are as follows:
  1. At the beginning of the crossover process we have two "parents". For example, in a problem of eight candidates to be assigned to five positions the solutions could be:

     $$S_1 = (8, 3, 4, 6, 1), \qquad S_2 = (6, 2, 4, 5, 7).$$

  2. First, we keep the repeated candidates and those that are in these positions on the other solutions in the offspring. Thus, we obtain

     $$S_1 = (8, \ , 4, 6, \ ), \qquad S_2 = (6, \ , 4, 5, \ ).$$

  3. Second, we assign random uniformly the remaining candidates to the offspring. Two resulting solutions could be:

     $$S_1 = (8, 2, 4, 6, 1), \qquad S_2 = (6, 3, 4, 5, 7).$$

Finally, after the crossover process, we have obtained two solutions that are feasible to the problem.

*4.2.5. Mutation operator*

The intention of this operator is to add diversity to the solutions. Then we must make differences among the two types of problems.

- *Assignment problems*: the mutation used is the exchange mutation between two positions of the solution. An example could be:

  $$S_1 = (2, 4, 5, 3, 1), \qquad S_1' = (2, 3, 5, 4, 1).$$

- *Selection problems*: we propose to use two different mutations, one like the previous type and other that introduces individuals not contained in the solution, for example:

  $$S_1 = (2, \overset{\downarrow}{4}, 5, 7, 9), \qquad S_1' = (2, 1, 5, 7, 9).$$

  and for their application we select one of them randomly.

*4.2.6. Halt criteria for the best solution search*

The proposal is for the algorithm to go through a number of generations specified by the user until the best solution is found. Moreover, in order not to lose good solutions, the characteristic termed *elitism* (Goldberg, 1989) has been introduced. This procedure consists of keeping the best individual from a population in successive generations unless and until some other individual succeeds in doing better in respect of suitability. In this way, the best solution for a previous population is not lost until outclassed by a more suitable solution.

As explained, application of the model proposed here allows an assignment–selection process to be carried out. It takes into account possible links among positions, several skills required and linguistic valuations.

## 5. Applications

One of the straightest applications of this model is staff selection. When personnel managers have to fill some jobs there are several variables under consideration. Firstly, we have to consider the competencies necessary to develop the job. Obviously not all the competencies have the same importance. Moreover, usually, the jobs are not independent, therefore a relationship among them could appear. Finally, all these information could be represented in a more accurate way using linguistic variables.

An other possible application could be suppliers selection. The objective is to select the supplier with the right technology, the right quality, the right capacity to make the quantities needed, the right financial terms, etc. This must be repeated for each of the materials or service required by the firm. Also, the materials or services required could not be independents, appearing as relationships. As in the previous problem, all the information could be characterised by linguistic values.

Others applications could be to select salesmen to sales regions, programmers to software projects, machines to tasks, capitals to investments, locations to factories, etc.

### 5.1. Practical application: staff selection

Among all of the possible assignment–selection problems (jobs to machines, requirements to suppliers, regions to salesmen, etc.), we have to select a staff selection problem. This deals with the choice of staff for a branch office of a banking institution. In this way, an attempt was made to demonstrate the usefulness that the model being proposed in this paper could have for real problems from the business world.

Let it be imagined that a banking firm wishes to open a new branch. The first step is to determine which posts are to be filled, and what status in terms of urgency each is to have in relation to the selection process. Thus, we might have:

| *Post number* | *Name* | *Importance* $(IP_j)$ |
|---|---|---|
| 1 | Branch manager | Essential |
| 2 | Supervisor | Fairly high |
| 3 | Administrative officer | Moderate |
| 4 | Administrative clerk | Low |
| 5 | Counter clerk/Teller | Very low |

For each post, thanks to a number of studies, the skills which must be developed and the weighting that each has for the position in question are known, as it is shown in Table 1.

In addition, the last piece of information needed in setting up these posts would be the

Table 1

| $IC_{ij}$ | Post 1 | Post 2 | Post 3 | Post 4 | Post 5 |
|---|---|---|---|---|---|
| Directing | Essential | – | – | – | – |
| Authorising/delegating | Fairly high | – | – | – | – |
| Integrity | Moderate | – | – | – | – |
| Fixing objectives | High | – | – | – | – |
| Strategic vision | Fairly high | – | – | – | – |
| Collecting information | – | Low | Very high | – | – |
| Analysing problems | – | High | – | – | – |
| Checking on procedures | – | Fairly high | – | – | – |
| Multitasking | – | Very high | Fairly low | – | – |
| Knowledge of organisation | – | Moderate | – | – | – |
| Mathematical ability | – | Moderate | – | Fairly high | – |
| Team work | – | – | Moderate | – | Moderate |
| Flexibility | – | – | High | – | Fairly low |
| Specialisation | – | – | Fairly high | – | – |
| Commercial orientation | – | – | – | Moderate | Very high |
| Personal charm | – | – | – | Low | Fairly high |
| Spoken communication | – | – | – | High | – |
| Customer orientation | – | – | – | Fairly high | Very high |

Table 2

| $RP_{ij}$ | Post 1 | Post 2 | Post 3 | Post 4 | Post 5 |
|---|---|---|---|---|---|
| Post 1 | – | Fairly high | High | Moderate | Fairly low |
| Post 2 | Fairly high | – | Moderate | Moderate | Low |
| Post 3 | Low | Very high | – | Very high | High |
| Post 4 | Low | Moderate | Very high | – | Very high |
| Post 5 | Fairly low | Moderate | Fairly high | Very high | – |

relationships among the post and the importance set on such relationships, as is shown in Table 2. This matrix is not symmetric due to the hierarchy among the post, but in other assignment–selection problems could be considered in this way.

Once the posts involved in the selection procedure have been determined, the candidates must next be considered. Let it be imagined that there are eight people who might be able to take on the jobs arising in the new branch.

| *Candidate* | *Name* |
|---|---|
| Candidate 1 | C.1 |
| Candidate 2 | C.2 |
| Candidate 3 | C.3 |
| Candidate 4 | C.4 |
| Candidate 5 | C.5 |
| Candidate 6 | C.6 |
| Candidate 7 | C.7 |
| Candidate 8 | C.8 |

For each one it is necessary to find out by some appropriate means the levels in each of the skills required for the posts, as shown in Table 3.

Finally, as there are links between the posts, the candidates must be looked at in order to find out the relationships that there would be among them, as shown in Table 4. This matrix could be symmetric if we consider the same appreciation of both individuals.

### 5.2. GA-based selection process

In this section we show the GA-based selection process of this example. So, for the purposes of application of the operational model, the parameters used in finding the solution by means of the model proposed were:

| | |
|---|---|
| Number of generations | 50 |
| Number of individuals | 100 |
| Crossover probability | 50% |
| Mutation probability | 30% |

It should be pointed out that the use of a high mutation probability was motivated by the need to bring new individuals into the chains, since if this were not so all that would be obtained would be the best combination of those initially considered whose passed the first selections.

In the practical example analysed the final solution obtained was:

| | |
|---|---|
| Post 1: Branch manager | Candidate: C.8 |
| Post 2: Supervisor | Candidate: C.6 |
| Post 3: Administrative officer | Candidate: C.2 |
| Post 4: Administrative clerk | Candidate: C.3 |
| Post 5: Counter clerk/Teller | Candidate: C.5 |

The graph of the evolution of the best individual in each generation is displayed in Fig. 2.

## 6. Concluding remarks

The results obtained from this work fall into two clusters. The first consists of the formulation of an assignment–selection model that could be adapted to the problem under consideration. The second is to present an application to staff selection that tries to be as real as possible.

In addition, as a proposal for future work, this research has backed the interest in using natural linguistic operators (LWA and LOWA) with the aim of handling linguistic information without having to transform it into a semantic representation (Herrera and Herrera-Viedma, 1997).

Table 3

| $N_{ij}$ | C.1 | C.2 | C.3 | C.4 | C.5 | C.6 | C.7 | C.8 |
|---|---|---|---|---|---|---|---|---|
| Directing | Very high | Very high | Low | High | High | High | Fairly high | Very high |
| Authorising | Fairly high | Fairly high | Moderate | Fairly high | Fairly high | Moderate | Moderate | High |
| Team work | Moderate | Fairly high | Moderate | Fairly low | Low | High | Moderate | Fairly high |
| Flexibility | High | High | Fairly low | Low | Fairly high | Low | Low | Moderate |
| Integrity | High | High | Low | Moderate | Fairly low | Fairly high | Moderate | Fairly high |
| Collecting information | Very low | Moderate | Moderate | Fairly low | Lowest | High | Fairly low | Lowest |
| Analysing problems | Fairly high | Fairly high | Low | High | Moderate | Fairly high | High | Very high |
| Fixing objectives | Very high | Very high | Moderate | High | Fairly low | Very high | Fairly high | Fairly high |
| Checking on procedures | High | High | Low | Moderate | Very low | Fairly high | High | Low |
| Multitasking | High | High | Moderate | Fairly high | Low | Fairly high | Low | Fairly high |
| Knowledge of the organization | Low | Fairly high | Moderate | Moderate | Very low | Moderate | Low | Fairly Low |
| Strategic vision | Fairly high | Fairly high | Low | High | Lowest | High | Fairly low | Very high |
| Specialist | Very low | Moderate | Moderate | Fairly low | Lowest | Fairly high | Low | Lowest |
| Commercial orientation | Lowest | Low | Low | Low | High | Moderate | Moderate | Moderate |
| Personal charm | Very low | Moderate | Moderate | Moderate | Fairly high | Very high | Lowest | Low |
| Spoken communication | Very low | Fairly high | Low | Very low | Fairly low | High | Moderate | Low |
| Customer orientation | Moderate | Moderate | Moderate | Low | High | Fairly high | Fairly low | Very low |
| Mathematical ability | Fairly low | Fairly low | High | Low | Very high | Moderate | Lowest | High |

Table 4

| $RC_{ij}$ | C.1 | C.2 | C.3 | C.4 | C.5 | C.6 | C.7 | C.8 |
|---|---|---|---|---|---|---|---|---|
| C.1 | – | Very good | Bad | Good | Moderate | Very bad | Moderate | Fairly bad |
| C.2 | Very bad | – | Bad | Moderate | Moderate | Good | Moderate | Very bad |
| C.3 | Very good | Fairly good | – | Bad | Good | Moderate | Good | Bad |
| C.4 | Very bad | Good | Moderate | – | Bad | Good | Moderate | Moderate |
| C.5 | Very good | Good | Good | Bad | – | Good | Fairly bad | Very bad |
| C.6 | Very good | Good | Moderate | Bad | Good | – | Moderate | Bad |
| C.7 | Bad | Good | Good | Fairly good | Very good | Fairly good | – | Fairly bad |
| C.8 | Bad | Fairly good | Good | Very good | Moderate | Fairly good | Moderate | – |

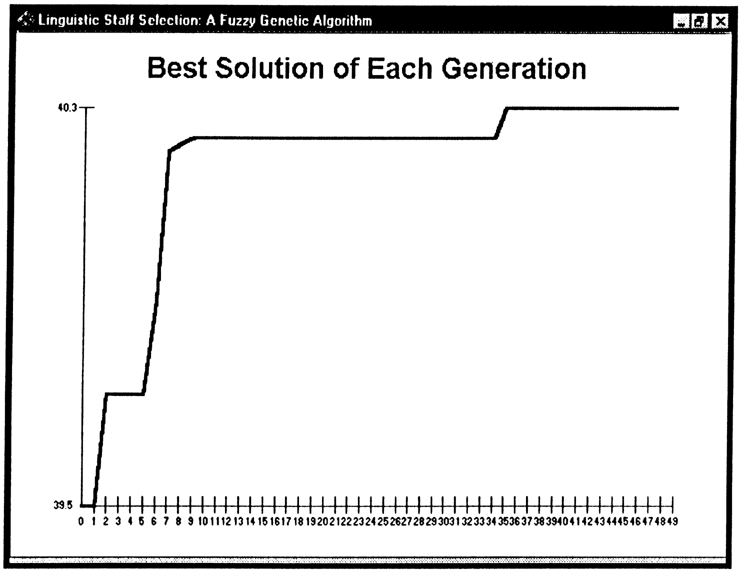


Fig. 2. Evolution of the best solution.

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